Beating 1/N with Factor Investing

V. DeMiguel
London Business School

A. Martin-Utrera
Lancaster U. Management School

F.J. Nogales
U. Carlos III de Madrid

R. Uppal
CEPR and Edhec

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Theory of mean-variance portfolios is beautiful

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Results implementing mean-variance portfolios are painful

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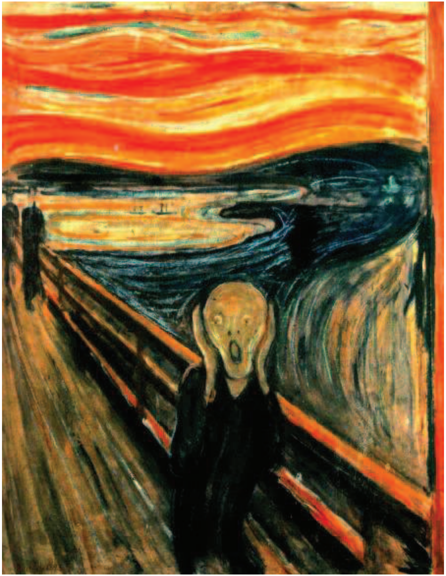


The 1/N paper

The Review of Financial Studies, 2009

Optimal Versus Naive Diversification: How Inefficient is the 1/*N* Portfolio Strategy?

Victor DeMiguel
London Business School

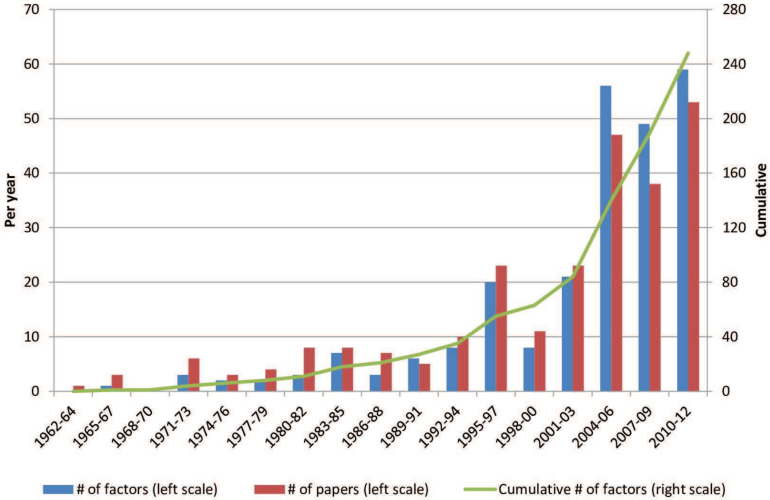
Lorenzo Garlappi
University of Texas at Austin

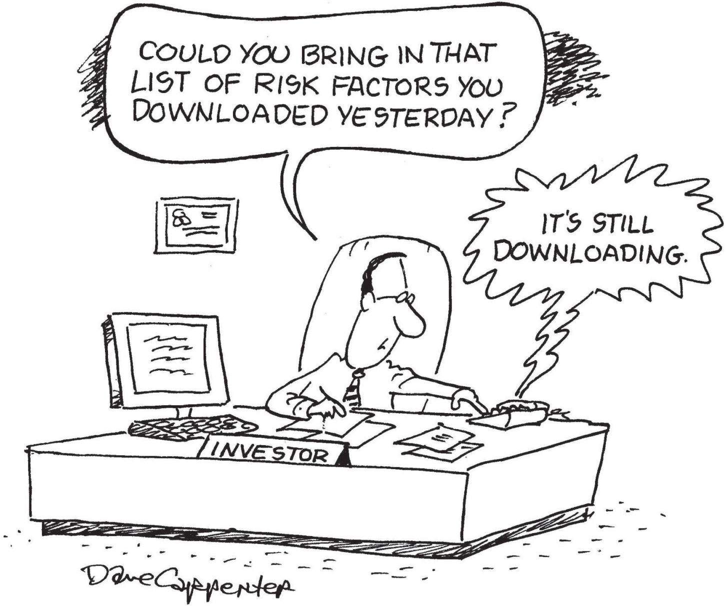
Raman Uppal
London Business School and CEPR

Beating 1/N with Factor Investing

300 factors?

Harvey et al. (2015)




COULD YOU BRING IN THAT LIST OF RISK FACTORS YOU DOWNLOADED YESTERDAY?
IT'S STILL DOWNLOADING.
INVESTOR
Dave Carpenter

How many are really important?

- More than 300 factors offered to explain cross section of stock returns: Harvey et al. (2015); McLean and Pontiff (2015)
- Cochrane's 2010 AFA presidential address
  - Which characteristics really provide independent information about average returns?
  - How many of these new factors are really important?
  - Can we again account for N independent dimensions of expected returns with $F < N$ factor exposures?

Factors models

(#) Factors	authors	market	size	value	mom.	invest.	profit.
3	Fama and French (1992)	✓	✓	✓			
4	Jegadeesh and Titman (1993)	✓	✓	✓	✓		
4	Novy-Marx (2013)	✓		✓	✓		✓
4	Hou et al. (2014)	✓	✓			✓	✓
5	Fama and French (2015)	✓	✓	✓		✓	✓
10	Lewellen (2014)						
24	Green et al. (2014)						

What we do

- Literature takes return-prediction perspective:
  - Cross-sectional (Fama-MacBeth) regressions, and
  - Time-series (Fama-French) regressions.

- We take an investment perspective:
  - Collect data for 51 firm-specific characteristics.
  - Compute parametric portfolios of Brandt et al. (2009):
    1. designed to exploit firm-specific characteristics,
    2. account for transaction costs.
  - **In sample:** test significance of characteristics for investment.
  - **In sample:** effect of transaction costs.
  - **Out of sample:** evaluate the gains from exploiting the characteristics.

Research questions

Q1: Which characteristics are significant for investment and why?

Q2: What is the effect of transaction costs?

Q3: How large are the out-of-sample gains from exploiting these characteristics?

What we find

Q1: Which and why?

- (1) unexpected quarterly earnings, (2) return volatility, (3) asset growth, (4) 1-month momentum, and (5) gross profitability increase mean returns and reduce risk of portfolio of characteristics.
- (6) Beta only reduces risk.

Q2: Effect of transaction costs?

- **Increase** number of significant characteristics to 15.
- Combining characteristics reduces transaction costs by 65%.

Q3: How large are the gains?

- Big-data parametric portfolios.
- Sharpe ratio of our strategy is
  - 140% higher than that of market portfolio, and
  - 100% higher than parametric portfolios with traditional characteristics: size, book-to-market, and momentum.

Data

Data

- Combine CRSP, Compustat, and I/B/E/S from Jan 1980 to Dec 2014.
- All firms in NYSE, AMEX, and NASDAQ exchanges:
  - drop firms with negative book to market,
  - drop firms below 20th percentile of market capitalization.
- 51 firm-specific characteristics; 100 characteristics in Green et al. (2014) after dropping characteristics with missing observations.
- Winsorize characteristics cross sectionally.
- Standardize characteristics so that they have a cross-sectional mean of zero and standard deviation of one: long-short portfolio.

Parametric portfolios

Parametric portfolios

	Firm-specific characteristics		
Benchmark portfolio	**Value long-short**	**Momentum long-short**	**Size long-short**
0.09%	0.01%	-0.02%	0.03%
0.05%	-0.02%	+0.01%	-0.01%
0.21%	-0.03%	+0.12%	0.13%
.	.	.	.
.	.	.	.
.	.	.	.
0.15%	0.03%	-0.02%	-0.01%

Parametric portfolios

$$\begin{array}{ccccccccc}
\text{Parametric portfolio} & & \text{Benchmark portfolio} & & \text{Value long-short} & & \text{Momentum long-short} & & \text{Size long-short} \\
\begin{pmatrix} 0.05\% \\ 0.05\% \\ 0.17\% \\ \cdot \\ \cdot \\ \cdot \\ 0.17\% \end{pmatrix} & = & \begin{pmatrix} 0.09\% \\ 0.05\% \\ 0.21\% \\ \cdot \\ \cdot \\ \cdot \\ 0.15\% \end{pmatrix} & + \Theta_1 & \begin{pmatrix} 0.01\% \\ -0.02\% \\ -0.03\% \\ \cdot \\ \cdot \\ \cdot \\ 0.03\% \end{pmatrix} & + \Theta_2 & \begin{pmatrix} -0.02\% \\ +0.01\% \\ +0.12\% \\ \cdot \\ \cdot \\ \cdot \\ -0.02\% \end{pmatrix} & + \Theta_3 & \begin{pmatrix} 0.03\% \\ -0.01\% \\ 0.13\% \\ \cdot \\ \cdot \\ \cdot \\ -0.01\% \end{pmatrix}
\end{array}$$

Choose θ_1, θ_2, and θ_3 to optimize mean-variance utility net of transaction costs.

Q1.

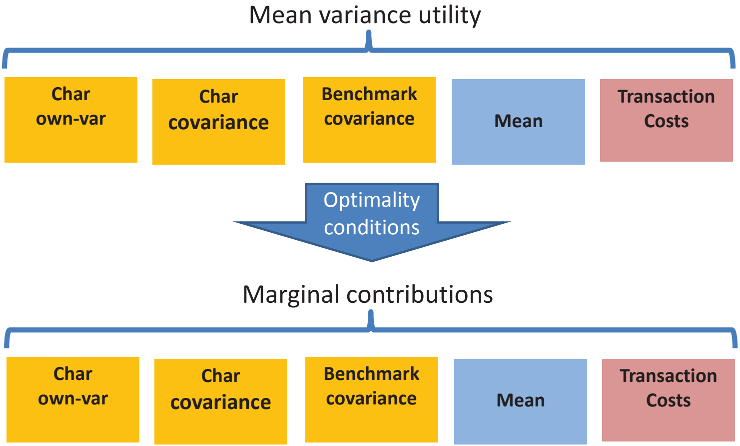
Which characteristics are significant and why?

Which characteristics are significant and why?

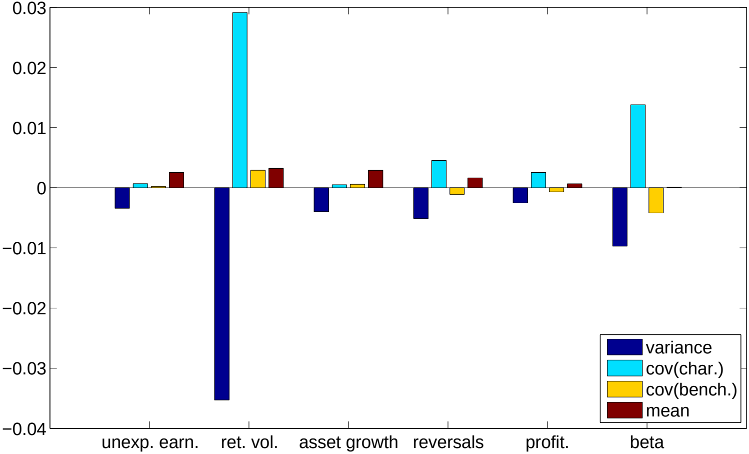
Significant characteristic	Increases mean	Reduces risk
1. unexpected quarterly earnings	✓	✓
2. return volatility	✓	✓
3. asset growth	✓	✓
4. 1-month momentum (reversals)	✓	✓
5. gross profitability	✓	✓
6. beta	✗	✓

- First five characteristics are significant because they increase mean return and help to reduce the risk of the portfolio of characteristics.
- Beta is significant because although its mean return is nearly zero, it diversifies the portfolio of characteristics.

Dissecting the parametric portfolios



Which characteristics are significant and why?

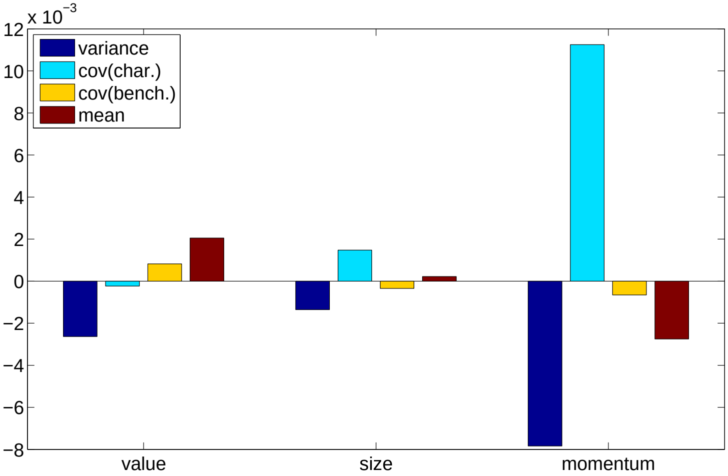


Why are traditional characteristics not significant?

Significant characteristic	Increases mean	Reduces risk
1. 12-month momentum	✓	✗
2. Book to market (value)	✓	✗
3. Size	✗	✓

- Momentum and book to market are not significant because they do not help to diversify the portfolio of characteristics.
- Size not significant because its mean return is not substantial.
- Significance depends on diversification benefits as much as on mean return.

Why are traditional characteristics not significant?



How are traditional characteristics correlated?

	value	size
size	-0.05	
momentum	-0.08	0.20

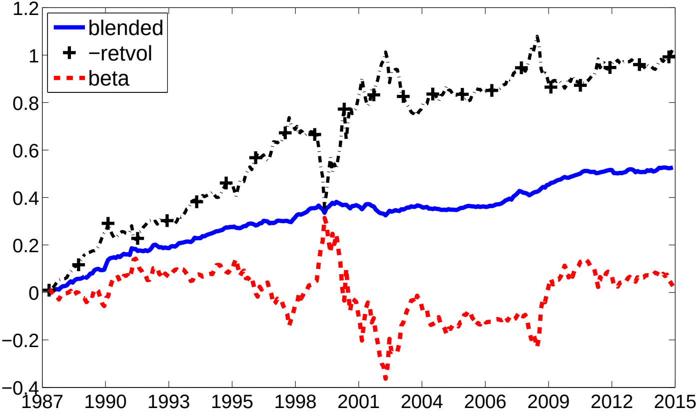
- Traditional characteristics are uncorrelated.
- They explain variability.

How are significant characteristics correlated?

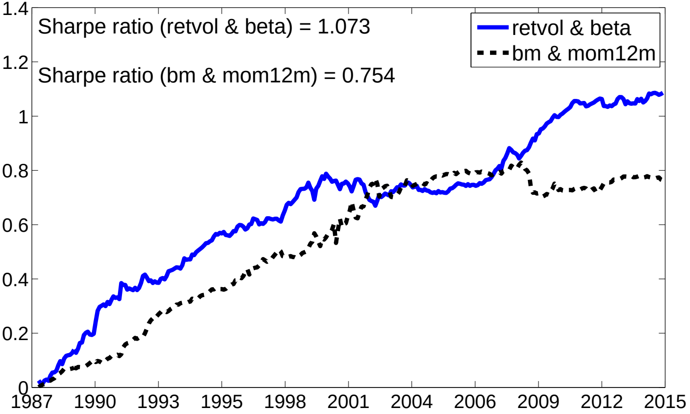
	unexp. earn.	ret. vol.	asset growth	reversals	profit.
ret. vol.	−0.43				
asset growth	−0.08	0.22			
reversals	0.18	−0.18	−0.33		
profit.	−0.18	0.45	0.56	−0.23	
beta	−0.36	0.93	0.33	−0.26	0.54

- Some of the six most significant characteristics are highly correlated.
- High correlation allows one to use them to reduce risk by hedging.
- Return volatility and beta are highly positively correlated, but beta has negligible mean return. Nearly perfect hedge.

Blended strategies (i)



Blended strategies (ii)



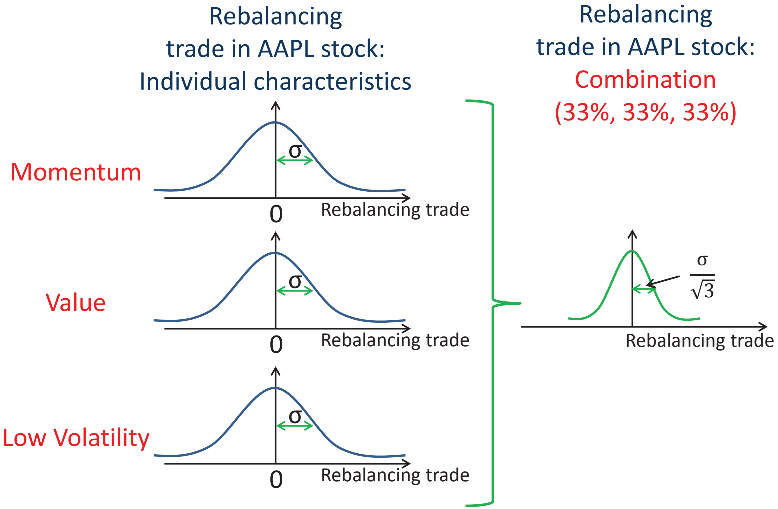
Q2.
What is the effect of transaction costs?

Effect of transaction costs

- Transaction costs increase number of significant characteristics to 15.

- Combining characteristics reduces transaction costs because of trading diversification.

Trading diversification



Effect of transaction costs

- Transaction costs increase number of significant characteristics to 15.
- Combining characteristics reduces transaction costs because of trading diversification.
  - Theoretically: Aggregate trading around $1/\sqrt{K}$ of that required to trade K characteristics in isolation.
  - Empirically: transaction costs reduced by around 65%.
- Short-term reversal remains significant with transaction costs.

Q3.

How large are the out-of-sample gains from exploiting characteristics?

Big data parametric portfolios

- Deal with *many* characteristics using a *lasso* constraint that:
  1. reduces impact of estimation error,
  2. identifies relevant characteristics.

- Lasso constraint:

$$\sum_{k=1}^{K} |\theta_k| \leq \delta,$$

  - δ is the lasso threshold.

How large are gains from exploiting characteristics?

Policy	Turnover	Mean	SD	SR
Panel A: Portfolios with no characteristics				
VW	0.050	0.085	0.150	0.567
1/N	0.134	0.085	0.177	0.482
Panel B: Portfolios with characteristics				
Traditional	0.754	0.145	0.215	0.675
Significant	1.065	0.223	0.166	**1.343**
Big-data	0.979	0.241	0.178	**1.356**

- Sharpe ratio of the big-data parametric portfolios is
  - 100% higher than that of traditional parametric portfolios;
  - 140% higher than that of the benchmark portfolio;
  - Similar to that of parametric portfolios from significant characteristics without look-ahead bias; that is, investor can identify ex-ante combinations of characteristics.

Robustness checks and conclusion

Robustness checks

1. Characteristics after publication: McLean and Pontiff (2015). ✓
2. Leverage constraints: 50% leverage is enough. ✓
3. Removing turnover constraints. ✓
4. Stock liquidity: gains from 60% of the smallest stocks. ✓
5. Shortsale constraints: parametric portfolios struggle.
6. Risk-aversion parameter. ✓
7. Time series regressions. ✓
8. Fama-MacBeth regressions.
   - beta and size are not significant.
   - Value and momentum are significant.

Conclusion

Q1: Which characteristics are significant and why?

- Six without transaction costs.
- risk diversification matters as much as mean return.

Q2: Effect of transaction costs?

- increase number of significant characteristics to 15.
- trading diversification reduces transaction costs by 65%.

Q3: How large are the gains?

- Big-data parametric portfolios.
- Investor can identify ex-ante combinations of characteristics.
- Sharpe ratio of our strategy is
  - 140% higher than that of market portfolio, and
  - 100% higher than parametric portfolios with traditional characteristics: size, book-to-market, and momentum.

Thank you!

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